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Planning carbon emission trading for Beijing's electric power systems under dual uncertainties

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ABSTRACT

In this study, a full-infinite interval-stochastic mixed-integer programming (FIMP) method is developed for planning carbon emission trading (CET) under dual uncertainties. FIMP has advantages in uncertainty reflection and policy analysis, particularly when the input parameters are provided as crisp and functional intervals as well as probabilistic distributions. The developed FIMP is applied to a real case study for managing carbon dioxide (CO_2) emissions with trading scheme of Beijing's electric power system (EPS). Electric power industry is one of the major sources of CO_2 emission in China. It is essential to accumulate relevant experience to provide a reliable basis for establishing a regional or national CET market, so as to prepare for docking with the international market. This is the first attempt to introduce CET scheme into Beijing's EPS to mitigate CO_2 emissions. The solutions for energy supply, electricity generation, carbon-quota allocation, and capacity expansion are obtained. They cannot only be used for formulating CO_2-reduction policies and assessing the associated economic implications in purchasing emission permits or bearing economic penalties, but also facilitate analyzing various policies when pre-regulated electricity-generation plans and pre-defined CO_2-emission schemes are violated.

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1. Introduction

Damage caused by global warming is happening far faster than experts predicted or anticipated. Potential threats generated by global warming may contain the increase in surface temperature, the change in the global climate, the rise in ocean level, even the disruption in food production [1,2]. The preponderance of emerging scientific evidence emissions of heat-trapping carbon dioxide (CO_2) from fossil fuels are tracking near the highest level considered by the Intergovernmental Panel on climate change [3]. Generally, CO_2 emission is closely related to human activities such as power generation, deforestation, transportation, as well as industrial, residential and commercial activities. CO_2 is discharged into the atmosphere from combustions of fossil fuels such as oil, natural gas, and coal as sources of energy. Since the Industrial Revolution, human activity has increased the amount of greenhouse gas (GHG) in the atmosphere, leading to increased radiative forcing from GHG. Amongst several environmental pollutants causing climate change, CO_2 is responsible for 58.8% of the GHG [4]. Meanwhile, the concentration of CO_2 has increased by 36% since 1750 [5]. Specially, fossil fuel burning in electric power system (EPS) has produced about three-quarters of the increase in CO_2 from human activity over the past 20 years, which is one of the major contributory factors for occurring global warming [3]. Since it is undeniable that many countries are still mainly dependent on fossil fuels to sustain their energy generation and supply, CO_2 emission will exacerbate global warming and lead to environmental destruction and health hazards which are already quite rampant nowadays.

Due to the harmful impact of excessive CO_2 emission, regulatory agencies have enacted strict regulations to limit their emissions. As a crucial international agreement, Kyoto Protocol was signed in 1997 to respond to global warming through reducing GHG emission. Recently, a milestone is marked in the Kyoto Protocol with the 2009 Climate Summit in Copenhagen, Denmark, with all participating countries further committed themselves in fulfilling the protocol's obligations before the commitment period due in 2012 [6]. Currently, there are several CET markets throughout the world, including clean development mechanism (CDM) project market, European Union greenhouse gas emission trading scheme (EU ETS), UK emissions trading group (ETG), Chicago climate exchange (CCX), and Australian climate exchange (ACX). In 2005, EU ETS was proposed as an allowance-based transaction which referred to the excess emission reduction trading under the total amount control among countries identified by Kyoto Protocol. As a major pillar of EU climate policy, EU ETS is the first large emission trading scheme in the world [7]. In 2010, emission trading revenue of EU ETS reached to $ 119.8 billion, accounting for 84% of the income of the global carbon trading. EU ETS covers 11,000 power stations and industrial plants in 30 countries, which are collectively responsible for 40% of its total GHG emissions. Under EU ETS, all members agree on their national emission caps which have to be approved by the EU commission, and then allocate allowances to their industrial operators, and validate the actual emissions in accordance with the relevant assigned amount [8].

As a market-based scheme, emissions trading could lead to a desired market transformation and encourage the application of energy efficient technologies, as well as ensure the achievement of emission reduction target [9]. During the period of 2005–2009, the EU ETS successfully reduced carbon emissions up to 5%, with a limited economic impact of less than 1% of total gross domestic product (GDP). The major British industries on average faced a cost increase amounting to 4% at a carbon price of $28.8 per metric ton [10]. Although no federal emissions trading market in United States, regional markets are in place or are under development, including the Regional Greenhouse Gas Initiative, Western Climate Initiative, and the Midwestern Greenhouse Gas Accord. According to these fundamental policies, a number of approaches are available to curb emissions and tackle climate change. For example, the cap and dividend system proposed by Peter Barnes is a market-based approach to reduce carbon emissions without reducing household incomes. Under this mechanism, fossil fuel supplies and emissions are capped. Polluters have to pay a premium to emit, which can be returned back to all citizens equally [11]. In another alternative approach, polluters voluntarily exchange the emissions within the cap and trade mechanism and pay extra taxes when emissions overrun the cap. Existing research works mainly focused on economic input–output modeling, life cycle assessment, and operating research models to examine the policy implications [12].

China is the second largest GHG emitter throughout the world, which pledges to reduce emissions per unit of economic output by 40–45% relative to 2005 level. However, with rapid economic development, China's energy consumption, especially electricity consumption, has grown swiftly. Coal-fired power occupies more than 75% of the total electricity generation in China, which presents particular phenomenon all around the world. Additionally, the amount of electricity generated from coal-fired power plant increased rapidly over recent years. For example, from 1991 to 2005, the amount has been maintained at 90–96%, which means that large amounts of CO_2 have been emitted. In 2005, carbon emissions from the Chinese power sector have reached 38.73% of total emissions of primary energy [13]. Electric power industry is one of the major sources of CO_2 emission in China. It is fundamental to accumulate relevant experience to provide a reliable basis for establishing regional and/or national CET markets [14]. However, Chinese current CET market is a CDM one [15]. Many cities (e.g., Beijing, Tianjin and Shanghai) have set up the environment or property exchange as the energy exchange trading platform for CDM projects. According to the studies of World Bank, China has potential for CO_2-emission reduction from 100 million ton to 200 million ton per year. It can provide more than half of the global CDM projects. In May 1998, China signed the Kyoto Protocol at United Nations Headquarters, and in August 2002, formally approved the Kyoto Protocol, which means that China start operation of the CDM projects. To enhance the effective management of the CDM projects and to ensure that their projects go into an orderly manner, Chinese government promulgated interim measures for the operation and management of the clean development mechanism project in June 2004. In October 2005, interim measures was amended, clean development mechanism project management approach is enacted. However, current CDM market is mainly a market for buyers. As a market for sellers, the project owners in developing countries are weak of negotiation right, which causes them being disadvantaged. At the same time,

it is also imperative to realize energy saving and CO_2-emission reduction, respond to international pressure and participate in international conventions roundly. Moreover, few research works concerning the impacts of CET on EPS of China have been proposed in a computable framework [14,16,17].

Previously, various mathematical models were undertaken for tackling the issues of CET; some of them were introduced for analyzing issues related to effectiveness and equality in CET [18–22]. For example, Bosello and Roson [18] formulated an integrated assessment model to analyze the CET and equity in international agreements, which explored the distributional consequences of alternative emission trading schemes. They found that the introduction of a competitive market for emission permits, especially when this market has no developing countries, would dramatically lower total abatement costs. Holtsmark and Mæstad [19] employed a numerical model to assess the significance of international emission trading for the oil, coal and gas markets. Yi et al. [20] constructed an intensity allocation model based on three indicators (i.e., per capita GDP, accumulated fossil fuel related CO_2 emissions and energy consumption per unit of industrial added value), where equity principles for target allocation were taken into account. Lu et al. [21] presented a carbon regulation based duopoly model to evaluate the effectiveness and equity of various carbon policies including emission standard, carbon tax, and emission trading.

Many researchers evaluated the economic efficiency of reducing carbon emission which was the goals of the EU ETS were criticized for not being ambitious enough [22]. Since it was generally either technically infeasible or economically impossible to design processes leading to zero emission of CO_2, authorities and decision makers always sleeked to control the CO_2 emission to level at which the effect was minimized [23]. Therefore, it is imperative to make a criterion of allowable levels of CO_2 emissions. Mathematical models were improved ceaselessly to response the changing factors related to emission permits [24–27]. For example, Haurie and Viguier [24] proposed a computable stochastic equilibrium model to represent possible competition between Russia and China on the international market of carbon emission permits; they analyzed the impact of this competition on the pricing of emission permits and on the effectiveness of the Kyoto and post-Kyoto agreements, without the United States participation. Rehdanz [25] developed a two-country game model to analyze the coordination of domestic markets for tradable emission permits, where countries determined their own emission reduction targets. Bristow et al. [26] developed a pooled model to explore the influence of key design attributes on the acceptability of a personal carbon trading scheme, where permit prices vary among different models because of differences in percentage reductions in emissions, baseline prices of carbon-energy, and price sensitivity of users [27]. In addition, ICLIPS (Integrated Assessment of Climate Protection Strategies) Climate Model (ICM) can be used to simulate the atmospheric retention and metabolism of CO_2. Linking the economic and the climate impact components in the ICLIPS framework, major greenhouse gases (including CO_2, CH_4, N_2O, halocarbons, SF6, tropospheric and stratospheric O_3, and stratospheric water vapor) as well as the radiative effects of aerosols originating from SO_2 emissions and from biomass burning were considered. Several researchers analyzed the equity issues and cost-effective emission trajectories based on the ICM [28–30].

Carbon emissions are easier to monitor and control from a limited number of centralised, large power stations than from millions of vehicles, small boilers and even ruminant animals. Accordingly, electricity sector has become a prime target where carbon emission controls are implemented and carbon emission mitigation is valued [31]. Previously, a number of researchers managed CO_2 emissions of EPS through CET scheme [32–37]. For example, Bonacina and Gullı‘ [32] analyzed the impact of CO_2-emission allowance trading on electricity pricing in short term. Bernard et al. [33] proposed a computable dynamic game model of the strategic competition between Russia and developing countries (mainly represented by China). Linares et al. [34] presented an oligopolistic generation-expansion model for the electricity sector. Chappin and Dijkema [35] presented an agent-based model to elucidate the effect of CET on the decisions of power companies in an oligopolistic market; in power generation, the economic effect of CET was not sufficient to outweigh the economic incentives in choosing coal. Sadegheih [36] proposed an optimization model to search for solutions to power network planning under the CET program, which possessed the ability to minimize the total cost with cost-effective and environmentally friendly manner. Koo et al. [37] proposed a robust optimization approach to plan sustainable energy systems of South Korea, which could help decision makers to determine the optimal capacities of power plants and/or carbon capture and storage, as well as volumes of emissions trading that could meet the required emission level and satisfy energy demand from various user-sections with minimum costs and maximum robustness.

In practical CET planning problems, a variety of complexities and uncertainties exist among different electricity-generation activities and their socio-economic and environmental implications [38–41]. In CET programs, uncertainties often arise due to inconstant commitments or changes of emission trading regulatory [42–47]. For example, CO_2 discharged from various electricity-generation activities (e.g., power plant, storage hydroelectric plant, or biomass power plant) can be influenced by some uncertain events (e.g., emission limitation), which may fluctuate time to time. Meanwhile, errors in estimated modeling parameters (e.g., economic penalty) could be possible sources of uncertainties. These complexities have placed many EPS management problems beyond the conventional optimization methods. Therefore, it is indispensable to inject more and more momentum to the EPS planning, including considerations for diversity of energy activities, structure of electricity generations, variation of system conditions, uncertainty of impact factors, dynamics of capacity expansion, as well as the associated environmental implication [48]. As a result, a few research efforts were conducted for dealing with various uncertainties in CET programs [46,49,50]. For example, Monni et al. [49] estimated uncertainties in different emissions trading schemes; according to their results, uncertainty in emissions from the EU15 and the EU25 included in the first phase of the EU emissions trading scheme (2005–2007) was $\pm 3\%$ (at 95% confidence interval relative to the mean value). Chen et al. [50] developed a two-stage inexact-stochastic programming model for planning GHG-emission trading within the electrical-power systems. Li et al. [46] proposed an interval-fuzz y two-stage stochastic programming method for planning CET under uncertainty, where three trading schemes were considered based on different trading participants.

The most previous optimization models were formulated through conventional interval-parameter programming (IPP) approach. Nevertheless, the conventional IPP has difficulties when the right-hand sides of a model are highly uncertain, especially with uncertainties expressed as possibilistic and/or probabilistic distributions, which may lead to the loss of valuable information in many real-world decision-making problems [51]. Additionally, IPP can only solve the problems containing crisp interval coefficients $[a, b]$, whose lower- and upper-bounds (i.e., a and b) are both deterministic and definitely known. Stochastic mathematical programming (SMP) is effective for decision problems whose coefficients (input data) are uncertain but could be represented as chances or probabilities, which has been

extensively applied to energy systems planning [52]. Two-stage stochastic programming (TSP) is a typical SMP method, which is an effective alternative for tackling problems where an analysis of policy scenarios is desired and the right-hand-side coefficients are random with known probability density functions (PDFs) [53]. In practical planning problems, it is important to expression the relationship between mathematical parameter and their economic influence in CET. The definition of crisp interval is not suitable for all cases where the two bounds may be associated with the external impact factors expressed as functional interval [$f(a)$, $g(b)$], where $f(a)$ and $g(b)$ are the functions of a and b, respectively. An attractive technique that could tackle functional intervals was full-infinite programming (FIP), which was proposed to deal with the uncertainties expressed as both crisp intervals and functional intervals.

Therefore, the objective of this study is to develop a full-infinite interval-stochastic mixed-integer programming (FIMP) method in response to the above challenges. Then, a FIMP-based carbon emission trading (FIMP-CET) model will be formulated for managing CO_2 emissions of Beijing's electric power system (EPS) with trading scheme. In the FIMP-CET model, emission-permit limits will be allocated to each power plant and the total CO_2-emission amount cannot be exceeded. If actual emission amount less than the allowed permit, the power plant can sold its excess CO_2 permit to achieve economic benefit; on the contrary, it has to buy the emission permits from the others or subject to heavy economic penalties from the local government. The modeling results will be used for generating a range of decision alternatives under various system conditions, and thus helping decision makers to discern optimal power-generation patterns, and gain deep insights into the tradeoffs between CO_2 emission and economic objective.

2. Methodology

Two-stage stochastic programming (TSP) method is effective for problems where an analysis of policy scenarios is desired and the related data are mostly uncertain [54–56]. In TSP, the first-stage decision is to be made before uncertain information is revealed, whereas the second-stage one (recourse) is to adapt to the previous decision based on the further information; the second-stage decision is used to minimize "penalties" that may appear due to any infeasibility [47,50]. The main advantage of TSP is its capacity in dealing with recourse, where corrective actions can be taken after a random event has taken place. A general TSP model can be formulated as follows:

$$z = \min C^T X + E_{\omega \in \Omega}[Q(X,\omega)]$$

subject to:

$$x \in X \tag{1a}$$

with

$$Q(x,\omega) = \min f(\omega)^T y$$

subject to:

$$D(\omega) y \geq h(\omega) + T(\omega) x \tag{1b}$$

$$y \in Y$$

where $X \in R^{n_1}$, $C \in R^{n_2}$ and $Y \in R^{n_2}$. Here, ω is a random variable from space (Ω, F, P) with $\Omega \in R^k, f: \Omega \to R^{n_2}, h: \Omega \to R^{m_2}, D: \Omega \to R^{m_2 \times n_2}$, and $T: \Omega \to R^{m_2 \times n_1}$. By letting random variables (i.e., ω) take discrete values ω_h with probability levels p_h (h = 1,2,..., ν and $\sum p_h = 1$), the above TSP can be equivalently formulated as a linear programming model as follows:

$$\text{Min} f = C_{T_1} X + \sum_{h=1}^{\nu} p_h D_{T_2} Y \tag{2a}$$

subject to:

$$A_r X \leq B_r, \quad r = 1,2,\ldots,m_1 \tag{2b}$$

$$A_t X + A'_t Y \geq w_h, \quad t \in M, \quad M = 1,2,\ldots,m_2, \quad h = 1,2,\ldots,\nu \tag{2c}$$

$$x_j \geq 0, \quad x_j \in X, \quad j = 1,2,\ldots,n_1 \tag{2d}$$

$$y_{jh} \geq 0, \quad y_{jh} \in Y, \quad j = 1,2,\ldots,n_2 \tag{2e}$$

Obviously, model (2) can deal with uncertainties in the right-hand sides presented as probability distributions when coefficients in the left-hand sides and in the objective function are deterministic. However, in real-world decision-making problems, the quality of information that can be obtained is mostly not satisfactory enough to be presented as probabilities. Such complexities cannot be solved through model (2). Generally, interval-parameter programming (IPP) approach is effective in tackling uncertainties expressed as interval values with known lower and upper bounds but unknown distribution functions. Therefore, through incorporating IPP and TSP within a general optimization framework, a hybrid two-stage stochastic programming linear model can be formulated as follows [56]:

$$\text{Min} f^{\pm} = C^{\pm}_{T_1} X^{\pm} + \sum_{h=1}^{\nu} p_h D^{\pm}_{T_2} Y^{\pm} \tag{3a}$$

subject to:

$$A^{\pm}_r X^{\pm} \leq B^{\pm}_r, \; r = 1, \; 2, \; \ldots, \; m_1 \tag{3b}$$

$$A^{\pm}_t X^{\pm} + A'^{\pm}_t Y^{\pm} \leq w^{\pm}_h, \quad t = 1,2,\ldots,m_2; \qquad h = 1,2,\ldots,\nu \tag{3c}$$

$$x^{\pm}_j \geq 0, \quad x^{\pm}_j \in X^{\pm}, \quad j = 1,2,\ldots,n_1 \tag{3d}$$

$$y^{\pm}_{jh} \geq 0, \quad y^{\pm}_{jh} \in Y^{\pm}, \quad j = 1,2,\ldots,n_2; \qquad h = 1,2,\ldots,\nu \tag{3e}$$

where $A^{\pm}_r \in \{R^{\pm}\}^{m_1 \times n_1}$, $A^{\pm}_t \in \{R^{\pm}\}^{m_2 \times n_2}$, $B^{\pm}_r \in \{R^{\pm}\}^{m_1 \times n_1}$, $C^{\pm}_r \in \{R\}^{1 \times n_1}$, $D^{\pm}_r \in \{R\}^{1 \times n_2}$, $X^{\pm} \in \{R^{\pm}\}^{n_1 \times 1}$, $Y^{\pm} \in \{R^{\pm}\}^{n_2 \times 1}$ and $\{R^{\pm}\}$ denote a set of crisp interval parameters and/or variables; superscripts '−' and '+' represent lower and upper bounds of the interval values, respectively [57–60]. In model (3), the decision variables are divided into two subsets: the first-stage decision variables $X^{\pm}$ that must be determined before the random variables are disclosed, and recourse variables $Y^{\pm}$ that can be determined after the random variables are disclosed. In the model, decision variables are divided into two subsets: Those that must be determined before random variables are disclosed and those (recourse variables) that will be determined after the uncertainties are disclosed.

Model (3) can handle uncertainties expressed as probability distributions as well as account for economic penalties with recourse against any infeasibility; however, it cannot address uncertainty expressed as functional intervals in the objective and constraints. In real-world decision-making problems, functional interval is defined as an interval with its lower and upper bounds being functions of an independent variable. It is indicated that the lower- and upper-bounds of the crisp interval can vary with its independent variables. In this study, crisp interval coefficients mean the conventional intervals, such as [a, b], whose lower and upper bounds (i.e., a and b) are both deterministic and definitely

known. This is based on the assumption that these interval coefficients are unchanged even if they could be affected by associated impact factors. Thus, despite the effectiveness of the previous methods in solving models containing interval-parameters, they are still limited for tackling functional intervals. An attractive technique that can tackle both crisp intervals and functional intervals is semi-infinite programming (SIP). However, SIP can only resolve problems with merely infinite constraints in deterministic environment, while FIP can address crisp and functional intervals with infinite objectives and constraints. Consequently, when the coefficients in objective function and constraints are all allowed to be functional intervals and/or crisp intervals, a full-infinite interval-stochastic mixed-integer programming (FIMP) model can be formulated as follows:

$$\mathrm{Min}\, f^{\pm} = C_{T_1}^{\pm}(\tau_i)\, X^{\pm} + \sum_{h=1}^{\nu} p_h D_{T_2}^{\pm} Y^{\pm} \quad \text{for all } \tau_i \in [\tau l, \tau u] \tag{4a}$$

subject to:

$$A_r^{\pm}(\tau_i) X^{\pm} \le B_r^{\pm}(\tau_i), \quad r = 1,2,\ldots,m_1 \tag{4b}$$

$$A_t^{\pm} X^{\pm} + A_t'^{\pm} Y^{\pm} \le w_h^{\pm}, \quad t = 1,2,\ldots,m_2; \qquad h = 1,2,\ldots,\nu \tag{4c}$$

$$x_j^{\pm} \ge 0, \quad x_j^{\pm} \in X^{\pm}, \quad j = 1,2,\ldots,n_1 \tag{4d}$$

$$y_{jh}^{\pm} \ge 0, \quad y_{jh}^{\pm} \in Y^{\pm}, \quad j = 1,2,\ldots,n_2; \qquad h = 1,2,\ldots,\nu \tag{4e}$$

where $X^{\pm}$ (j=1, 2,…,n) are decision variables; $C_{T_1}^{\pm}(\tau_i)$, $A_r^{\pm}(\tau_i)$, and $B_r^{\pm}(\tau_i)$are functional interval parameters in objective and constraints. $C_{T_1}^{-}(\tau_i)$ and $C_{T_1}^{+}(\tau_i)$ (j=1, 2,…,k) are positive for all $\tau_i$values; $C_{T_1}^{-}(\tau_i)$ and $C_{T_1}^{+}(\tau_i)$ (j=k+1, k+2,…,n) are negative functions for all τ_i values. As a result, an optimized set of $x_{jt}^{\pm}$ values can be identified by having u_{jt} as decision variables; this optimized set may correspond to minimized system cost under uncertain generation targets $x_{jt}^{\pm}$ [56]. In detail, let $x_{jt}^{\pm} = x_{jt}^{-} + \Delta x_{jt} u_{jt}$, where $\Delta x_{jt} = x_{jt}^{+} - x_{jt}^{-}$, and $u_{jt} \in [0,1]$. When $x_{jt}^{\pm}$ approach their lower bounds (i.e., $u_{jt}=0$), a relatively low cost would be obtained; however, a higher penalty may have to be paid when the demand is not satisfied. Conversely, when $x_{jt}^{\pm}$ reach their upper bounds (i.e., $u_{jt}=1$), a higher cost would be generated but, at the same time, a lower risk of violating the promised targets (and thus lower penalty). Then, model (4) can be transformed into two deterministic submodels. When the objective is to be minimized, the submodel corresponding to f^{-} can be firstly formulated:

$$\begin{aligned}\mathrm{Min}\, f^{-} = &\sum_{j=1}^{k_1} c_j^{-}(\tau_i) x_j^{-} + \sum_{j=k_1+1}^{n_1} c_j^{+}(\tau_i) x_j^{+} \\ &+ \sum_{j=1}^{k_2}\sum_{h=1}^{\nu} p_{jh} d_j^{-} y_{jh}^{-} + \sum_{j=k_2+1}^{k_2}\sum_{h=1}^{\nu} p_{jh} d_j^{-} y_{jh}^{-} \\ &\text{for all } \tau_i \in [\tau l, \tau u]\end{aligned} \tag{5a}$$

subject to:

$$\sum_{j=1}^{k_1} |a_{rj}(\tau_i)|^{+} \mathrm{Sign}(a_{rj}^{+}(\tau_i)) x_j^{-} + \sum_{j=k_1+1}^{n_1} |a_{rj}(\tau_i)|^{-} \mathrm{Sign}(a_{rj}^{-}(\tau_i)) x_j^{+} \le b_r^{+}(\tau_i), \forall r \tag{5b}$$

$$\begin{aligned}&\sum_{j=1}^{k_1} |a_{tj}|^{+} \mathrm{Sign}(a_{tj}^{+}) x_j^{-} + \sum_{j=k_1+1}^{n_1} |a_{rj}|^{-} \mathrm{Sign}(a_{tj}^{-}) x_j^{+} \\ &+ \sum_{j=1}^{k_2} |a'_{tj}|^{-} \mathrm{Sign}(a'^{+}_{tj}) y_{jh}^{-} + \sum_{j=k_2+1}^{n_2} |a'_{tj}|^{-} \mathrm{Sign}(a'^{-}_{tj}) y_{jh}^{+} \ge \omega_h^{-}, \quad \forall t,h\end{aligned} \tag{5c}$$

$$x_j^{-} \ge 0, \quad j = 1,2,\ldots,k_1 \tag{5d}$$

$$x_j^{+} \ge 0, \quad j = k_1+1, \quad k_1+2,\ldots,n_1 \tag{5e}$$

$$y_{jh}^{-} \ge 0, \quad \forall h; \qquad j = 1,2,\ldots,k_2 \tag{5f}$$

$$y_{jh}^{+} \ge 0, \quad \forall h; \qquad j = k_2+1, \quad k_2+2,\ldots,n_2 \tag{5g}$$

where $x_j^{\pm}, j=1,2,\ldots,\ k_1$ are interval variables with positive coefficients in the objective function; $x_j^{\pm}, j=k_1+1, k_1+2,\ldots,n_1$ are interval variables with negative coefficients; $y_{jh}^{-} \ge 0$, $j=1,2,\ldots,k_2$ and $h=1,2,\ldots,\nu$ are random variables with positive coefficients in the objective function; $y_{jh}^{\pm} \ge 0$, $j=k_2+1,k_2+2,\ldots,n_2$ and $h=1$, $2,\ldots,\nu$ are random variables with negative coefficients. Solutions of $x_{jopt}^{-}(j=1,2,\ldots,k_1)$, $x_{jopt}^{+}(j=k_1+1,\ k_1+2,\ldots,n_1)$, $y_{jhopt}^{-}(j=1,2,\ldots,k_2)$ and $y_{jhopt}^{+}(j=k_2+1,k_2+2,\ldots,n_2)$ can be obtained through submodel (5). Based on the above solutions, the second submodel corresponding to f^{+} can be formulated as follows:

$$\begin{aligned}\mathrm{Min} f^{+} = &\sum_{j=1}^{k_1} c_j^{+}(\tau_i) x_j^{+} + \sum_{j=k_1+1}^{n_1} c_j^{+}(\tau_i) x_j^{-} + \sum_{j=1}^{k_2}\sum_{h=1}^{\nu} p_{jh} d_j^{+} y_{jh}^{+} + \sum_{j=k_2+1}^{k_2}\sum_{h=1}^{\nu} p_{jh} d_j^{+} y_{jh}^{-} \\ &\text{for all } \tau_i \in [\tau l, \tau u]\end{aligned} \tag{6a}$$

subject to:

$$\sum_{j=1}^{k_1} |a_{rj}(\tau_i)|^{-} \mathrm{Sign}(a_{rj}^{-}(\tau_i)) x_j^{+} + \sum_{j=k_1+1}^{n_1} |a_{rj}(\tau_i)|^{-} \mathrm{Sign}(a_{rj}^{+}(\tau_i)) x_j^{-} \le b_r^{-}(\tau_i), \quad \forall r \tag{6b}$$

$$\begin{aligned}&\sum_{j=1}^{k_1} |a_{tj}|^{-} \mathrm{Sign}(a_{tj}^{-}) x_j^{+} + \sum_{j=k_1+1}^{n_1} |a_{rj}|^{+} \mathrm{Sign}(a_{tj}^{+}) x_j^{-} \\ &+ \sum_{j=1}^{k_2} |a'_{tj}|^{-} \mathrm{Sign}(a'^{-}_{tj}) y_{jh}^{+} + \sum_{j=k_2+1}^{n_2} |a'_{tj}|^{+} \mathrm{Sign}(a'^{+}_{tj}) y_{jh}^{-} \ge \omega_h^{+}, \forall t,h\end{aligned} \tag{6c}$$

$$x_j^{-} \ge x_{jopt}^{-}, \quad j = 1,2,\ldots,k_1 \tag{6d}$$

$$0 \le x_j^{+} \le x_{jopt}^{+}, \quad j = k_1+1, \quad k_1+2,\ldots,n_1 \tag{6e}$$

$$y_{jh}^{+} \ge y_{jhopt}^{-}, \quad \forall h; \qquad j = 1,2,\ldots,k_2 \tag{6f}$$

$$0 \le y_{jh}^{+} \le y_{jhopt}^{+}, \quad \forall h; \qquad j = k_2+1, \quad k_2+2,\ldots,n_2 \tag{6g}$$

solutions of $x_{jopt}^{+}(j=1,2,\ldots,k_1)$, $x_{jopt}^{-}(j=k_1+1,k_1+2,\ldots,n_1)$, $y_{jhopt}^{+}(j=1,2,\ldots,k_1)$, and y_{jhopt}^{-}, $\forall h$; $j=k_2+1,k_2+2,\ldots,n_2$ can be obtained. Through solving submodels (5) and (6), interval solutions associated with probability information can be obtained as

follows:

$$x_{jopt}^{\pm} = [x_{jopt}^{-}, x_{jopt}^{+}], \forall j \tag{7a}$$

$$y_{jhhopt}^{\pm} = [y_{jhhopt}^{-}, y_{jhhopt}^{+}], \forall j, h \tag{7b}$$

$$f_{opt}^{\pm} = [f_{opt}^{-}, f_{opt}^{+}], \forall j \tag{7c}$$

3. Case study

3.1. Statement of problems

Beijing is the capital of China; with the increasing economic development and population growth, the amount of energy demand has rapid growth in the last decades. According to Statistics Bureau of Beijing, total energy consumption amounted to 42.29 million tonne of coal equivalent in 2001, while 65.70 million tonne of coal equivalent in 2009. In 2010, the amount of the city's energy consumption reached to 65.70 million tons of coal equivalent. Coal consumption accounts for 30.3% of the total energy consumption. According to the statistic data, all of natural gas, 97% of coal, 80% of refined oil, and 70% of electricity need to be transferred from the neighboring provinces [61,62]. Particularly, electricity mainly depends on ''West-East Electricity Transmission Project'', and an implemented project named ''West-to-East Gas Transport'' helps deliver natural gas to the city. The energy redeployment pattern has bonded its own economic operation and the external supply together, which could arouse many unpredictable factors and increase the risk of economic development in Beijing. The city's power demand is growing with the rapid development of economic and continually improvement of people's living standard, which also promotes the swift development of it power-generation industry. As illustrated in Fig. 1, the total amount of electricity consumption in Beijing increased from 51.01 billion kW h in 2004 to 83.09 billion kW h in 2010. Elasticity ratio of electricity consumption has reached more than one in recent years, which means that the growth rate of electricity demand is far greater than the speed of domestic economic development. Although Beijing's energy end-consumption structure has improved in recent years, its energy consumption is still relied heavily on coal. The proportion of both coal and coke occupies 40%, and 75% of electricity generated from coal-fired conversion technique. The proportion of coal in the total energy is gradually decreasing, and the total amount of coal is continuing to increase. Because of this, a large amount of CO_2 emission was caused by coal consumption, and electric power plants become one of the main sources of CO_2 contribution in China [13,16].

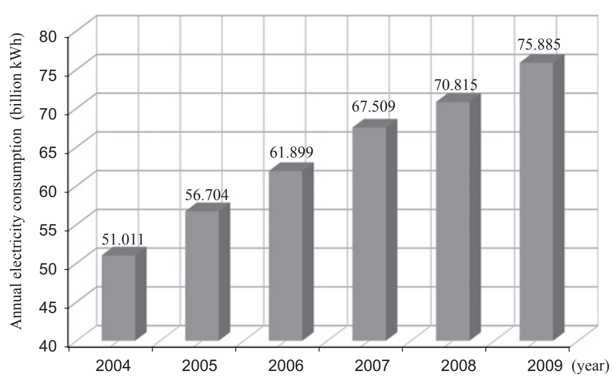

Fig. 1. Annual electricity consumption of Beijing from 2004 to 2009.

Currently, the city still faces a number of challenges to achieve the CO_2-reduction goals, and those pressures come from both domestic and overseas. Firstly, the contradiction between electricity demands and CO_2-reduction goals would be increasingly prominent. Secondly, energy structure is needed to further adjust and optimize. Thirdly, the superiority of renewable energy has not been fully played by now. EPS is one of the major sectors for emission CO_2. As a consequence, trying to develop carbon trading in EPS, stimulating the enthusiasm of the CO_2 reduction through market means, and reducing system cost by using advanced technology will vigorously promote electric power industry restructuring and industrial upgrading. Meanwhile, China has been viewed to be one of the most promising emission markets for reducing GHG, although there is no emission reduction assignment. This study attempts to introduce CET into the Beijing's electric power market to deal with these questions: (1) how to determine initial distribution of permits and sector coverage for Beijing's domestic power market; (2) how to quantify the final system cost of each power conversion technology under CET; (3) how to ascertain the amount of electricity supply and CO_2 mitigation. Fig. 2 presents the CET scheme of power generation system in Beijing. The relationships among government, fuel market, power producers, carbon market, electricity market, economic information as well as energy flow have been presented. As is shown in the figure, it is obvious that uncertainties would influence the process of modeling CO_2 emission in EPS of Beijing. For example, the amount of CO_2 emission generated from the electricity generation sector may vary because of the various electricity demands; distinctly, for such a large system, the coefficients related to cost and benefit information is not sufficient. An integrated energy and environmental management system can be characterized by one or several sources (i.e., power conversion technology) generally. A large amount of CO_2 emission from these power plants may lead to adverse impacts on climate change. For example, increasing amount of CO_2 in the atmosphere may affect weather condition changes, sea/land ice cover decreases, biodiversity changes, and ecosystem changes.

3.2. Modelling formulation

In CET management, it is imperative to identify desired schemes for energy-flow allocation, electricity-supply and CO_2 emission permits with minimized system cost and maximized system reliability. Conventional and renewable energy resources with limited availabilities are employed (including raw coal, washed coal, coal products, coal oven gas, other coal gas, diesel oil, fuel oil, refinery dry gas, natural gas, oil products, coking products, heating power and other energy sources). Seven power-conversion technologies are taken into consideration, such as coal-fired power, hydropower, pumped storage, wind power, photovoltaic power, waste generation and biomass power. In order to reduce the cost for CO_2 treatment, emission trading is considered for each power conversion technology. A target quantity of CO_2 emission quota is allocated to each power conversion technology. If this quantity is satisfied, the EPS will bring net benefits. If this quantity exceeds the regulated level, it is necessary to take measures to decrease the CO_2 emission. In response to such regulation, the power plants have to optimize CO_2 treated to achieve a minimized system cost while to satisfy the GHG-emission requirement. Through the CET program, each power plant can sell credit to other power plants with higher electric power profitability. The CO_2 emission permits can thus be reallocated to the most efficient power plants instead of proportionally allocated to each power plant. Consequently, the developed FIMP method can be used to address these problems, leading to a FIMP-based carbon emission trading (FIMP-CET) model. The objective

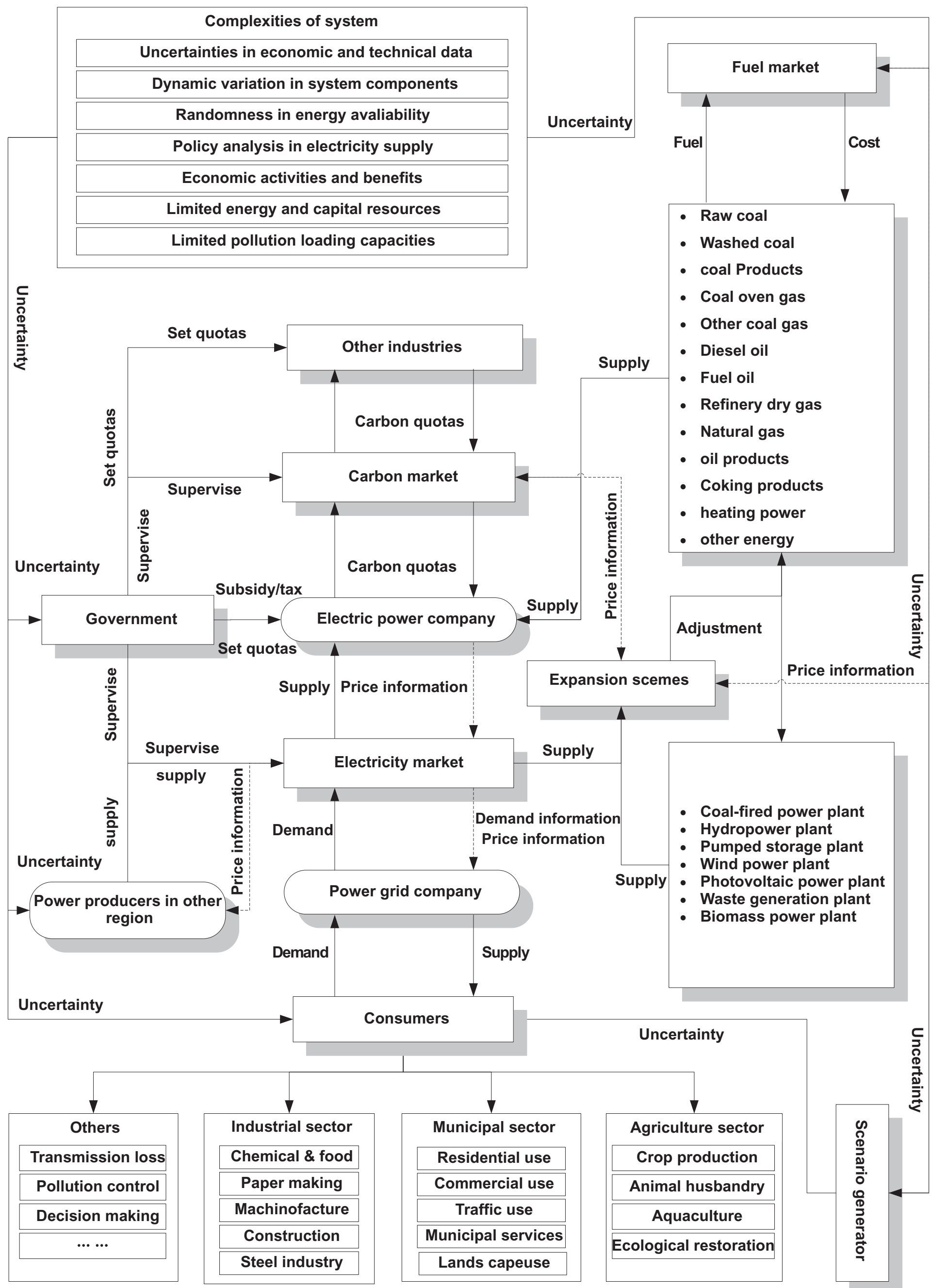

Fig. 2. Carbon trading in electric power systems of Beijing.

function of the FIMP-CET model can be formulated as follows:

$$\text{Min}\, f^{\pm} = (1)+(2)+(3)+(4)+(5)+(6)+(7) \qquad (8-1)$$

(1) Cost for purchasing energy:

$$\sum_{i=1}^{13}\sum_{k=1}^{3} CBN_{ik}^{\pm}(\gamma_k^{\pm}) \times ZHX_{ik} \times XNL_{ik}^{\pm} \qquad (8-1a)$$

(2) Operating cost for electricity generation:

$$\sum_{n=1}^{7}\sum_{k=1}^{3}\sum_{q=1}^{3} L \times (PFD_{nk}^{-} + y_{nk} \times \Delta PFD_{nk}^{-} + YPL_{nkq}^{\pm} \times YDA_{nkq}) \times ODC_{nk}^{\pm}(\alpha_{nk}^{\pm}) \qquad (8-1b)$$

(3) Penalty for electricity shortage:

$$\sum_{h=1}^{3} p_h \times WCC_h^{\pm}(v_h^{\pm}) \times OSE_h^{\pm} \qquad (8-1c)$$

(4) Cost for capacity expansion:

$$\sum_{n=1}^{7}\sum_{k=1}^{3}\sum_{q=1}^{3} L \times YPL_{nkq}^{\pm} \times YDA_{nkq} \times YDI_{nk}^{\pm}(\gamma_k^{\pm}) \qquad (8-1d)$$

(5) Cost for electricity transmission:

$$\sum_{n=1}^{7}\sum_{k=1}^{3}\sum_{q=1}^{3} L \times (PFD_{nk}^{-} + y_{nk} \times \Delta PFD_{nk}^{-} + YPL_{nkq}^{\pm} \times YDA_{nkq}) \times CUT_k^{\pm} \qquad (8-1e)$$

Table 1
Purchase cost for energy source (10^6 RMB ¥/PJ).

	Time period		
	$k=1$	$k=2$	$k=3$
Raw coal	$[22.90\ (1+\gamma_i)^t,\ 25.80\ (1+\gamma_i)^t]$	$[25.80\ (1+\gamma_i)^t,\ 28.60\ (1+\gamma_i)^t]$	$[28.90\ (1+\gamma_i)^t,\ 32.50\ (1+\gamma_i)^t]$
Washed coal	$[29.80\ (1+\gamma_i)^t,\ 33.30\ (1+\gamma_i)^t]$	$[29.80\ (1+\gamma_i)^t,\ 33.30\ (1+\gamma_i)^t]$	$[29.80\ (1+\gamma_i)^t,\ 33.30\ (1+\gamma_i)^t]$
Coal products	$[29.80\ (1+\gamma_i)^t,\ 29.80\ (1+\gamma_i)^t]$	$[29.80\ (1+\gamma_i)^t,\ 29.80\ (1+\gamma_i)^t]$	$[29.80\ (1+\gamma_i)^t,\ 29.80\ (1+\gamma_i)^t]$
Coal oven gas	$[29.80\ (1+\gamma_i)^t,\ 29.80\ (1+\gamma_i)^t]$	$[29.80\ (1+\omega_i)^t,\ 29.80\ (1+\gamma_i)^t]$	$[29.80\ (1+\gamma_i)^t,\ 29.80\ (1+\gamma_i)^t]$
Other coal gas	$[116.60\ (1+\gamma_i)^t,\ 118.70\ (1+\gamma_i)^t]$	$[118.60\ (1+\gamma_i)^t,\ 122.60(1+\gamma_i)^t]$	$[119.80\ (1+\gamma_i)^t,\ 125.70\ (1+\gamma_i)^t]$
Diesel oil	$[143.30\ (1+\gamma_i)^t,\ 148.00\ (1+\gamma_i)^t]$	$[148.00\ (1+\gamma_i)^t,\ 154.30\ (1+\gamma_i)^t]$	$[156.20\ (1+\gamma_i)^t,\ 138.50\ (1+\gamma_i)^t]$
Fuel oil	$[131.10\ (1+\gamma_i)^t,\ 133.50\ (1+\gamma_i)^t]$	$[136.20\ (1+\gamma_i)^t,\ 140.70\ (1+\gamma_i)^t]$	$[142.10\ (1+\gamma_i)^t,\ 84.40\ (1+\gamma_i)^t]$
Refinery dry gas	$[29.80\ (1+\gamma_i)^t,\ 29.80\ (1+\gamma_i)^t]$	$[29.80\ (1+\gamma_i)^t,\ 29.80\ (1+\gamma_i)^t]$	$[29.80\ (1+\gamma_i)^t,\ 32.50\ (1+\gamma_i)^t]$
Natural gas	$[46.40\ (1+\gamma_i)^t,\ 50.00\ (1+\gamma_i)^t]$	$[60.41\ (1+\gamma_i)^t,\ 68.90\ (1+\gamma_i)^t]$	$[74.40\ (1+\gamma_i)^t,\ 32.50\ (1+\gamma_i)^t]$
Oil products	$[123.40\ (1+\gamma_i)^t,\ 128.20\ (1+\gamma_i)^t]$	$[131.40\ (1+\gamma_i)^t,\ 135.00\ (1+\gamma_i)^t]$	$[135.00\ (1+\gamma_i)^t,\ 138.50\ (1+\gamma_i)^t]$
Coking products	$[36.80\ (1+\gamma_i)^t,\ 50.00\ (1+\gamma_i)^t]$	$[47.40\ (1+\gamma_i)^t,\ 58.00\ (1+\gamma_i)^t]$	$[56.10\ (1+\gamma_i)^t,\ 84.40\ (1+\gamma_i)^t]$
Heating power	$[30.00\ (1+\gamma_i)^t,\ 47.40\ (1+\gamma_i)^t]$	$[30.00\ (1+\omega_i)^t,\ 32.00\ (1+\gamma_i)^t]$	$[30.00\ (1+\gamma_i)^t,\ 32.50\ (1+\gamma_i)^t]$
Other energy	$[64.14\ (1+\gamma_i)^t,\ 32.00\ (1+\gamma_i)^t]$	$[68.50\ (1+\omega_i)^t,\ 71.90\ (1+\gamma_i)^t]$	$[71.81\ (1+\gamma_i)^t,\ 76.10\ (1+\gamma_i)^t]$

Note: symbols γ_i and t denote the interest rate and time interval (from the time of data sources to this study).

(6) Cost for CO_2 reduction:

$$\sum_{n=1}^{7}\sum_{k=1}^{3}\sum_{q=1}^{3} L \times (PFD_{nk}^{-} + y_{nk} \times \Delta PFD_{nk}^{-} + YPL_{nkq}^{\pm} \times YDA_{nkq}) \times (CPN_k^{\pm} + SF_k \times CEE_k^{\pm} - SU_k^{\pm}) \quad (8-1f)$$

(7) Penalty for excess CO_2 emission:

$$\sum_{n=1}^{7}\sum_{k=1}^{3}\sum_{h=1}^{3} L \times p_h \times XCP_{nk}^{\pm} \times GMR_{nk}^{\pm} \quad (8-1g)$$

where $f^{\pm}$ is total cost for purchasing energy, electricity generation, penalty for electricity shortage, capacity expansion, electricity transmission, CO_2 reduction and penalty for excess CO_2 emission; i represents type of purchasing energy, where $i=1$ for raw coal; $i=2$ for washed coal; $i=3$ for coal products; $i=4$ for coal oven gas; $i=5$ for mixed coal gas; $i=6$ for diesel oil; $i=7$ for fuel oil; $i=8$ for refinery dry gas; $i=9$ for natural gas; $i=10$ for oil products; $i=11$ for coking product; $i=12$ for heating power; $i=13$ for other energy sources; n denotes power conversion technology, $n=1$ for coal-fired power; $n=2$ for hydropower; $n=3$ for pumped storage; $n=4$ for wind power; $n=5$ for photovoltaic power; $n=6$ for waste generation; $n=7$ for biomass power; k is planning period, $k=1, 2, 3$; L is planning time period (three years); q is capacity-expansion program; h is electricity-demand level, $h=1, 2, 3$; p_h is probability of demand-level h occurrence in period k (%);$XNL_{ik}^{\pm}$ is amount of energy supply from source i in period k (PJ); $OSE_h^{\pm}$ is the amount of electricity shortage (e.g., imported electricity) under electricity-demand level h (PJ); $XCP_{nk}^{\pm}$ is the amount of excess CO_2 generated from power conversion technology n in period k (10^3 t); $YPL_{qnk}^{\pm}$ is the binary variables for identifying whether or not a capacity expansion action of power conversion technology n under different expansion program q needs to be undertaken in period k; $PFD_{nk}^{\pm}$ is pre-regulated electricity target of via power conversion technology n which is promised to end-users in period k (PJ); $\triangle PFD_{nk} = PFD_{nk}^{+} - PFD_{nk}^{-}$, $PFD_{nk}^{+} = PFD_{nk}^{-} + \triangle PFD_{nk} \times y_{nk}$, $y_{nk} \in [0,1]$; $CBN_{ik}^{\pm}$ is purchase cost for energy source i in period k (10^6 RMB¥/PJ); $\gamma_k^{\pm}$ is interest rate in period k; $v_h^{\pm}$ is interest rate under variable electricity demand-level h; ZHX_{ik} is transform coefficient (PJ/10^3 t standard coal); $WCC_h^{\pm}$ is purchasing cost for importing power from other regions under variable electricity demand-level h (10^6 RMB¥/PJ); YDA_{qnk} is vexpansion capacity for conversion technology n under expansion program q in period k (MW); $YDI_{nk}^{\pm}$ is expansion cost for conversion technology n in period k (10^6 RMB¥/MW); $ODC_{nk}^{\pm}$ is operation cost for power conversion technology n in period k (10^6 RMB¥/PJ); $\alpha_{nk}^{\pm}$ is electricity equipment depreciation rate for conversion technology n in period k; $CUT_k^{\pm}$ is cost for electricity transmission in period k (10^6 RMB¥/PJ); $CPN_k^{\pm}$ is cost for reducing CO_2 emission in period k (10^6 RMB¥/PJ); SF_k is CO_2 reduction efficiency in period k; $CEE_k^{\pm}$ is cost for CO_2 emission in period k (10^6 RMB¥/PJ); $SU_k^{\pm}$ is financial subsidy in period k (10^6 RMB¥/PJ); $GMR_{nk}^{\pm}$ is operating cost for excess CO_2 released from power conversion technology n in period k (10^3 RMB¥/tonne).

Table 1 reveals the purchase cost for energy sources. In energy systems, energy prices are closely related to the volatility of interest rates and time intervals. For example, for long-term EPS planning, the purchase cost for energy source ($CBN_{ik}^{\pm}$) can be affected by the fluctuation of interest rates, leading to that the lower and upper bounds of purchase cost can vary with the interest rate. Under this situation, the concept of crisp interval may not be suitable for describing this uncertainty. Functional intervals can be defined as a lower- and an upper-bound, which are both functions of its associated impact factor, can be used to effectively reflect such an uncertainty. For example, if $CBN_{ik}^{\pm}$ is expressed as a functional interval of $[22.90\ (1+\gamma i)^t,\ 25.80\ (1+\gamma i)^t] \times 10^6$ RMB ¥/PJ; symbols γi and t denote the interest rate and time interval (from the time of data sources to this study), $CBN_{ik}^{\pm}$ is a function of interest rate, ranging between $22.90\ (1+\gamma i)^t \times 10^6$ RMB¥/PJ and $25.80\ (1+\gamma i)^t \times 10^6$ RMB¥/PJ. Therefore, the definition of functional interval can help reflecting modeling uncertainties with more complexities way and describing the real-world conditions with more efficiency way. The systems analysis methods can be able to reflect interactive, complex, dynamic and uncertain features of the CET management systems. The outputs would be interpreted to generate desired planning alternatives for a number of human activities, as well as the related policies and strategies.

The system cost is to be minimized subject to a set of constraints that describe various impact factors and their interactions. These constraints contain resource availability constraints, mass balance constraints, power demand-supply balance, CO_2 emission constraints, reallocated emission permits constraints, expansion capital constraints, integer-variable constraints, and nonnegative constraints. These constraints include a number of inequalities which define relationships among various decision variables and system conditions, which can be formulated as follows:

3.2.1. Resource availability constraints

$$\sum_{i=1}^{13}\sum_{k=1}^{3} XNL_{ik}^{\pm} \le RZO_{ik}^{\pm}, \quad \forall i,k \quad (8-2a)$$

Table 2
Electricity demands and optimal electricity supply scheme (PJ).

	Probability (%)	Time period		
		$k=1$	$k=2$	$k=3$
Electricity demands				
Low	60		[919.56, 5817.35]	
Medium	20		[1036.50, 6483.00]	
High	20		[1145.22, 7081.32]	
Optimal electricity supply				
Coal-fired power		[107.49, 111.79]	[117.96, 122.68]	[128.43, 133.56]
Hydropower		[30.14, 31.35]	[30.00, 31.20]	[38.52, 40.06]
Pumped storage		[4.36, 4.54]	[7.50, 7.81]	[10.64, 11.07]
Wind power		[7.54, 7.84]	[8.79, 9.14]	[10.05, 10.45]
Photovoltaic power		[21.35, 22.21]	[27.63, 28.74]	[33.91, 35.27]
Waste generation		[42.08, 43.76]	[44.17, 45.94]	[46.26, 48.11]
Biomass power		[247.82, 257.74]	[268.76, 279.51]	[289.69, 301.28]
Solution of electricity shortage				
Low	60		[207.31 479.22]	
Medium	20		[248.77, 525.01]	
High	20		[289.70, 579.81]	

where $RZO_{ik}^{\pm}$ denotes energy availability of energy type i in period k (10^4 t standard coal). This constraint represents that, for each power conversion technology in each period, the amount of energy utilization must be not less than the total available energy amounts.

3.2.2. Mass balance constraints

$$\sum_{i=1}^{13}\sum_{k=1}^{3} XNL_{ik}^{\pm} \times CZN_{ik}^{\pm} \geq \sum_{n=1}^{7}\sum_{k=1}^{3}(PFD_{nk}^{-}+y_{nk}\times\Delta PFD_{nk}^{-}), \quad \forall k, \; n=1 \tag{8-2b}$$

where $CZN_{ik}^{\pm}$ is the transfer coefficient for unit coal raw consumption for electricity production; Constraint (8-2b) specifies that the amount of generated electricity in power conversion technology must not exceed its existing and expanded capacities. Mass-balance constraint is established to ensure that the input energy is greater than the output one.

3.2.3. Constraints of power demand–supply balance

$$\sum_{n=1}^{7}\sum_{k=1}^{3}\sum_{q=1}^{3} L\times(PFD_{nk}^{-}+y_{nk}\times\Delta PFD_{nk}^{-}+YPL_{nkq}^{\pm}\times YDA_{nkq} \times h_k - SD_{nk}^{\pm}\times h_k + OSE_k^{\pm})\times(1-SL_k) \geq DE_h^p, \quad \forall h \tag{8-2c}$$

where h_k is electric generation hours in period k (hour); $SD_{nk}^{\pm}$ is the power lost for each power conversion technology in each planning period; DE_h^p represents random variable of total electricity demand of level h in period k (PJ). Constraint (8-2c) is generated for each sector to ensure that the energy outputs from the demand technologies be equal to the end-use energy demands. Table 2 depicts the electricity demands and their associated probabilities of occurrence. According to Beijing Statistics Bureau (from 1991 to 2011), three discrete target values (i.e., low, medium and high) are selected as the range of interval. Additionally, division of the targets into a number of predefined values associated with probabilities (20%, 60%, and 20%) can also meet the requirement of two-stage stochastic programming (TSP) [43,63].

3.2.4. CO_2 emission constraints

$$\sum_{n=1}^{7}\sum_{k=1}^{3}\sum_{q=1}^{3} L\times(PFD_{nk}^{-}+y_{nk}\times\Delta PFD_{nk}^{-}+YPL_{nkq}^{\pm}\times YDA_{nkq}\times h_k) \times AMR_{nk}^{\pm}\times(1-SF_k) \leq ES_k^{\pm}, \quad \forall k \tag{8-2d}$$

$$\sum_{n=1}^{7}\sum_{k=1}^{3}\sum_{q=1}^{3} L\times(PFD_{nk}^{-}+y_{nk}\times\Delta PFD_{nk}^{-}+YPL_{nkq}^{\pm}\times YDA_{nkq}\times h_k) \times AMR_{nk}^{\pm}\times(1-SF_k) \geq XCP_{nk}^{\pm}, \quad \forall n,k \tag{8-2e}$$

where $AMR_{nk}^{\pm}$ denotes emission amount of CO_2 for power conversion technology n in period k (10^3 t/PJ); $ES_k^{\pm}$ is the allowed amount of CO_2 in period k (10^3 t); constraints (8-2d) and (8-2e) set up limitations for the total amount of CO_2 emission s; they denote that the excess CO_2 generated from power conversion technology should conform the allowed amount of CO_2 formulated by the government.

3.2.5. Reallocated CO_2-emission permits constraints

$$\sum_{n=1}^{7}\sum_{k=1}^{3}\sum_{q=1}^{3} L\times[(PFD_{nk}^{-}+y_{nk}\times \varDelta PFD_{nk}^{-}+YPL_{nkq}^{\pm}\times YDA_{nkq}\times h_k) \times AMR_{nk}^{\pm} - XCP_{nk}^{\pm}] \leq ZFX_{nk}^{\pm}, \quad \forall n,k \tag{8-2f}$$

$$\sum_{n=1}^{7}\sum_{k=1}^{3}\sum_{q=1}^{3} ZFX_{nk}^{\pm} \geq (1-yt_k^{\pm})TFD_{nk}^{\pm}, \quad \forall n,k \tag{8-2g}$$

$$ZFX_{nk}^{\pm} \leq (1-\omega)\times TFD_{nk}^{\pm}, \quad \forall n,k \tag{8-2h}$$

$$ES_k^{\pm} = B_k^{\pm}\times l_n \times AMR_{nk}^{\pm}\times DE_k^{\pm}, \quad \forall n,k \tag{8-2i}$$

where $ZFX_{nk}^{\pm}$ is the reallocated CO_2 emission permit generated from power conversion technology n in period k (10^3 t); $TFD_{nk}^{\pm}$ represents the discharge limit of total CO_2 emissions for power conversion technology n in period k (10^3 t); ω is CO_2-reduction

efficiency level (percentage of reduced total CO_2 emission permit); $B_k^{\pm}$ is power demand and supply index in period k; l_n is amount of CO_2 emission loading per PJ electricity for power conversion technology n. In Beijing, each power conversion technology has a pre-regulated generation target. If the target is not exceeded, the system will be encountered the regular cost; otherwise, the system will be subject to penalties resulted from the extra labor, management, operation and maintenance costs, or capacity expansion and higher costs for importing clean energy. For example, in power plant, the amounts of CO_2 emissions vary qualitatively and quantitatively from one power plant to another, which can result in huge variations in the cost of achieving targets of emission limits. This difference in cost can also encourage managers of power plants to carry out carbon emissions trading scheme. In order to reduce the cost for CO_2 treatment, CET is considered for all the power plants. Based on the local CO_2 emission management policies, a target quantity of CO_2 emission quota is allocated to each power plant. If this quantity is satisfied, the power generation system will bring net benefit. If this quantity exceeds the regulated level, power plants will have to take measures to decrease the CO_2 emission. In response to such regulation, the power plants need to optimize CO_2 treated to achieve a maximized system net benefit while to satisfy the GHG emission requirement. Through the CET, each power plant can sell credit to other power plants with higher electric power profitability. The CO_2 emission permits can thus be reallocated to the most efficient power plants instead of proportionally allocated to each power plant. From a long-term planning view, decision-makers have to face a dilemma of either investing more funds on capacity expansion of existing facilities or turning to other energy production options or putting extra funds into energy imports at raised prices [50]. These constraints about reallocated CO_2-emission permits are used for guarantee the implement of CET.

3.2.6. Expansion capital constraints

$$\sum_{n=1}^{7}\sum_{k=1}^{3}\sum_{q=1}^{3} L \times YPL_{nkq}^{\pm} \times YDA_{nkq} \times YDI_{nk}^{\pm}(\gamma_{nk}^{\pm}) \le MN_{nk}^{\pm} \quad \forall n,k \tag{8 – 2j}$$

where $MN_{nk}^{\pm}$ denotes the expense for power plant expansion for power conversion technology n in period k (106 RMB¥); Constraint (8-2j) is formulated to secure sufficient financial capacities for satisfying production of a given energy, where expansion constraints describe the lower and upper bounds of capacity expandability.

3.2.7. Interval-integer variable constraints

$$YPL_{nkq}^{\pm}\begin{cases} =1; \text{ if capacity expansion is undertaken} \\ =0; \text{ if otherwise} \end{cases} \quad \forall n,k,q \tag{8 – 2k}$$

From a long-term planning point of view, the city's electricity demands keep increasing due to population increase and economic development. This tendency can lead to insufficient capacity to meet the overall electricity demands from multiple end-users. The related optimization analysis will require the use of integer variables to indicate whether a particular facility development or expansion option needs to be undertaken [63].

3.2.8. Nonnegative constraints for decision variables

$$XNL_{ik}^{\pm}, OSE_k^{\pm}, XCP_{nk}^{\pm}, ZFX_{nk}^{\pm} \ge 0 \tag{8 – 2l}$$

The above model can be solved according to the solution method as described in Section 2. In the above modeling formulation, pre-regulated electricity target ($PFD_{nk}^{\pm}$) are expressed as interval numbers. An optimized set of $PFD_{nk}^{\pm}$ values will be identified by having y_{nk} as decision variables; this optimized set may correspond to a minimized system cost. In detail, let $PFD_{nk}^{\pm} = PFD_{nk}^{-} + y_{nk} \times \Delta PFD_{nk}^{\pm}$, where $\Delta PFD_{nk} = PFD_{nk}^{+} - PFD_{nk}^{-}$ and $y_{nk} \in [0,1]$. As a result, when $PFD_{nk}^{\pm}$ approach their lower bounds (i.e., when $y_{nk} = 0$), a relatively low cost would be obtained; however, a higher penalty may have to be paid when the electricity demand is not satisfied. Conversely, when $PFD_{nk}^{\pm}$ reach their upper bounds (i.e., when $y_{nk} = 1$), a higher cost would be generated but, at the same time, a lower risk of violating the promised targets. The objective function [i.e., Eq. (8-1)] is to minimize the expected system cost. If the promised electricity target is delivered, a net cost to the local economy will be generated for each unit of electricity supply. However, if the promised electricity is not delivered, either the electricity must be obtained from higher-priced alternatives, or the demands must be curtailed with the costs of reduced industrial and/or agricultural productions. These would then result in an increase of system cost to each user. Fig. 3 presents the framework of FIMP-CET model of Beijing's EPS. In this system, different uncertainties are suffused in input data including price data, demand data, emission data and availability data. By solving the model, the schemes about energy supply, electricity supply, carbon quotas and capacity expansion would be generated. Moreover, excess and reallocated CO_2 can be achieved when the allowable CO_2 levels (as pre-regulated by authorities) exceed.

4. Result analysis

In this study, three time periods are considered, with each having an interval of 3 years. Over the 9-year planning horizon, an existing power generation system is available to meet electricity needs of the city. Facilities of coal-fired power plant, hydropower plant, pumped storage plant, wind power plant, photovoltaic power plant, waste generation plant and biomass power plant are available for power generation. The results may shed light on the advantages of the government's decision and even potentially cause a change in policy.

4.1. Carbon trading analysis

In this study, CET is considered for helping satisfy the GHG emission requirement of EPS. Based on local CO_2 emission management policies, trading amount of CO_2-emission permit would be allocated to each power plant. If CO_2 emission equal to (or less than) the pre-regulated quota, benefits would be achieved. In comparison, if CO_2 emission exceeds the pre-regulated quota, reduction measures should be adopted in power plants to decrease the CO_2 emission for avoiding high system cost. To response to such regulation, the power plants need to generate trading amount of CO_2-emission permit to achieve a minimized system cost while to satisfy the GHG emission requirement. Fig. 4 depicts the solutions of amount of CET by solving the FIMP-CET model. Coal-fired power plant would purchase partial CO_2-emission permit from other power plants (e.g., hydropower, pumped storage, wind power, photovoltaic power, waste generation and biomass power) over the planning horizon. For example, the amounts of CO_2 emissions purchased from other power plants would be $[4186.63, 5116.12] \times 10^3$ t in period 1, $[4159.19, 5067.86] \times 10^3$ t in period 2, and $[4145.48, 5019.59] \times 10^3$ t in period 3. Sellers would be the roles for hydropower, pumped storage, wind power, photovoltaic power, waste generation and

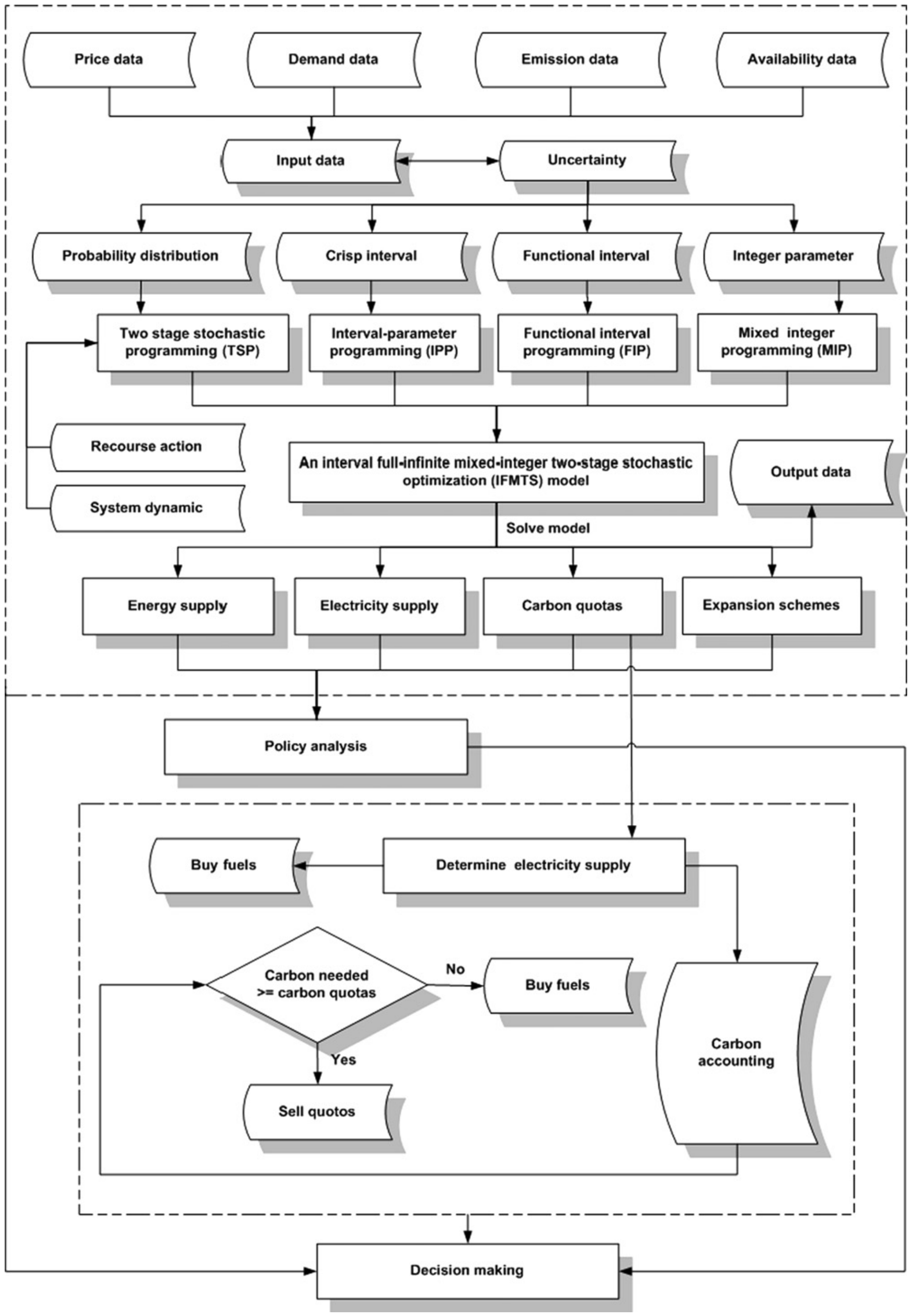

Fig. 3. Framework of FIMP-CET model of Beijing.

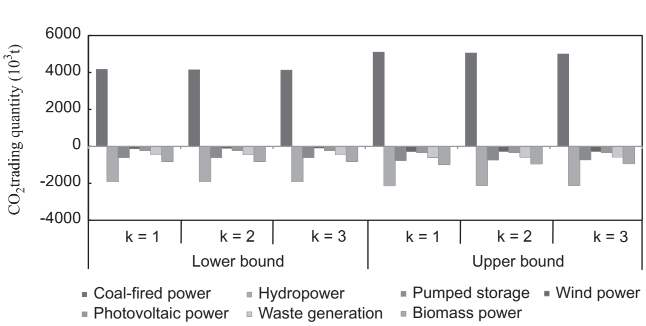

Fig. 4. Solution of trading amount of CO_2-emission permit.

biomass power plants. For example, for the hydropower plant, the amount of CO_2-emission permit sold to other power plants (e.g., coal-fired) would be $[1930.43, 2152.26] \times 10^3$ t, $[1930.43, 2131.95] \times 10^3$ t and $[1930.43, 2111.65] \times 10^3$ t during periods 1 to 3. For the biomass power plant, the amounts of CET would be $[816.56, 971.51] \times 10^3$, $[816.56, 962.34] \times 10^3$ and $[816.56, 953.18] \times 10^3$ t during periods 1 to 3. For the wind power plant, the amounts would be $[134.42, 290.79] \times 10^3$ t in period 1, $[106.99, 288.04] \times 10^3$ t in period 2, and $[93.27, 285.30] \times 10^3$ t in period 3. So, CO_2 emission permits can be reallocated to the most efficient power plants instead of proportionally allocated to each power plant.

4.2. Energy resources supply

Energy resources used in Beijing can be further divided into seven types, such as raw coal, washed coal, coal products, coal oven gas, other coal gas, diesel oil, fuel oil, refinery dry gas, natural gas, oil products, coking products, heating power and others. Table 3 reveals the results of optimal energy supply ($XNL_{ik}^{\pm}$) for ensuring the normal operation of EPS. According to the table, the amount of raw coal would decrease from period 1 to period 3. For example, the amount of raw coal would be [1668.24, 1868.43] PJ in period 1, [1526.54, 1724.99] PJ in period 2, and [1426.54, 1640.52] PJ in period 3. Such a drop is due to closure small-scale mining facilities for reaching stringent environmental requirement. The gap would be filled by imports from other energy systems, mostly from the Shanxi and Inner-Mongolia provincial energy systems. Meanwhile, for declining high external dependence of the energy utilization, the amount of diesel oil and fuel oil would distinctly decrease from period 1 to period 3. Natural gas has a dramatic growth among the whole planning horizon. For instance, the amount of natural gas would reach [393.66, 440.90] PJ in period 1, [501.74, 566.97] PJ in period 2, and [602.44, 692.81] PJ in period 3. Thus, natural gas would be one of the major energy sources in the future for the city. Consequently, the city's energy policies for enhancing energy supply capacity, speeding up the utilization of renewable energy, and increasing energy infrastructure investment are desired.

4.3. Electricity supply

Solutions of optimal electricity supply scheme can be interpreted based on the results presented in Table 2. Several power conversion technologies, including coal-fired power, hydropower, pumped storage, wind power, photovoltaic power, waste generation and biomass power. Managers would have to promise pre-regulated target values of electricity supply in order to satisfy the electricity demand objective. Among the power conversion technology, optimized electricity-generation target can be obtained. For example, biomass power would become the most competitive form of power generation in the near future. The amount of biomass power would increase from [247.82, 257.74] PJ in period 1 to [289.69, 301.28] PJ in period 3. The raise of biomass power generation would occur in whole planning horizon, which has an increase from 8.44% to 8.45%. For environmental consideration, the generation amount of coal-fired power will be tightened in a long-term period. For example, the generation amount of coal-fired power would be [107.49, 111.79] PJ in period 1, [117.96, 122.68] PJ in period 2, and [128.43, 133.56] PJ in period 3, respectively. What's more, by contrast with wind power, photovoltaic power and waste generation would have relatively wide development space. The amount of photovoltaic power grew steadily in the planning period, changing from [21.35, 22.21] PJ in period 1 to [33.91, 35.27] PJ in period 3. Moreover, the amount of electricity generated from waste power plant would go up with a dramatic rise from [42.08, 43.76] PJ in period 1 to [46.26, 48.11] PJ in period 3. This is a sharp increase of 9.93–9.94%. In addition, with the rapid economic growth, electricity demand is increasing year by year. Electricity generated from local power plant cannot meet such a huge demand for electricity consumption, and then electricity shortage ($OSE_k^{\pm}$) would occur. Thus, for filling the electricity demand gap, electricity would be imported from other regions, mostly from the Shanxi and Inner-Mongolia provincial energy systems. High electricity demand and the total amount of CO_2 emitted would be confined with a certain level during the planning periods. The amounts of imported electricity would be [207.31, 217.67] PJ in period 1, [248.77, 261.21] PJ in period 2, and [289.69, 304.18] PJ in period 3. The imported electricity occupied 7.61–18.40% of the total electricity generation under low electricity-demand level, 7.49–19.36% under medium electricity-demand level, and 7.57–20.19% under high electricity-demand level. Although electricity demand is huge, renewable energy generation contains enormous development potential. It is requisite to promote the utilization of renewable energy. As important measures to guarantee a nation's energy security, the development and utilization of renewable energy are crucial for supporting CO_2 emission reduction.

4.4. Capacity expansion

In EPS, existing capacity always cannot meet the electricity demands; as a result, facility expansion would be obtained through the FIMP-CET model to guarantee the electricity requirement use. Table 4 expresses the results of expansion schemes ($YPL_{qnk}^{\pm}$) and capacity investment ($MN_{nk}^{\pm}$). Capacity expansion in this study means to expand production scale of the existing power plant, to eliminate backward high energy-consumption equipment, and to promote energy-saving technologies and equipment. In period 1, hydropower capacity would be expanded to [80,90] MW; an additional capacity of [80,90] MW from wind power facilities would be installed, and the amount of capacity expansion for biomass power would reach to [80,90] MW as well. In period 2, hydropower capacity would be expanded to [120,130] MW, and an additional capacity of [120,130] MW from wind power facilities would achieve installed. In period 3,

Table 3
Solution of optimal energy supply (PJ).

	Time period		
	$k=1$	$k=2$	$k=3$
Raw coal	[1668.24, 1868.43]	[1526.54, 1724.99]	[1426.54, 1640.52]
Washed coal	[7.58, 8.48]	[9.23, 10.42]	[11.23, 12.91]
Coal products	[10.75, 12.04]	[7.20, 8.14]	[7.10, 8.17]
Coal oven gas	[1.93, 2.17]	[2.29, 2.58]	[2.49, 2.86]
Other coal gas	[34.94, 39.14]	[34.37, 38.84]	[34.35, 39.50]
Diesel oil	[0.65, 0.73]	[0.44, 0.49]	[0.45, 0.52]
Fuel oil	[10.41, 11.66]	[3.43, 3.87]	[4.22, 4.85]
Refinery dry gas	[2.07, 2.32]	[3.91, 4.42]	[3.75, 4.31]
Natural gas	[393.66, 440.90]	[501.74, 566.97]	[602.44, 692.81]
Oil products	[5.67, 6.35]	[6.10, 6.89]	[6.10, 7.02]
Coking products	[27.39, 30.68]	[22.90, 25.87]	[20.33, 23.38]
Heating power	[34.67, 38.83]	[58.09, 65.64]	[67.80, 77.97]
Other energy	[14.70, 16.46]	[15.60, 17.63]	[19.00, 21.85]

Table 4
Solution of expansion scheme and capacity investment.

	Time period		
	$k=1$	$k=2$	$k=3$
Expansion schemes (MW)			
Coal-fired power	[0, 0]	[0, 0]	[0, 0]
Hydropower	[80,90]	[120,130]	[0, 0]
Pumped storage	[0, 0]	[0, 0]	[0, 0]
Wind power	[80,90]	[120,130]	[0, 0]
Photovoltaic power	[0, 0]	[0, 0]	[150,160]
Waste generation	[0, 0]	[0, 0]	[0, 0]
Biomass power	[80,90]	[0, 0]	[120,130]
Capacity investment (10^9 RMB¥)			
Coal-fired power	[0, 0]	[0, 0]	[0, 0]
Hydropower	[11.76, 25.83]	[21.89, 37.32]	[0, 0]
Pumped storage	[0, 0]	[0, 0]	[0, 0]
Wind power	[104.52, 246.04]	[165.89, 284.31]	[0, 0]
Photovoltaic power	[0, 0]	[0, 0]	[1916.01, 1749.60]
Waste generation	[0, 0]	[0, 0]	[0, 0]
Biomass power	[53.57, 110.72]	[0, 0]	[139.35, 140.38]

the amount of capacity expansion for photovoltaic power would be [150,160] MW, and an additional capacity of [120,130] MW from biomass power facilities would achieve installed as well. In addition, capacity investment expenses related to interest rate were generated from the proposed model as shown in table. As a matter of fact, backward equipment would cause material waste, environmental pollution, as well as GHG emissions. As a result, after renewable energy generation expansions occur in the planning periods, the total capacity of the facilities would be sufficient to meet the increased electricity demand and the reduced CO_2 emission requirement.

4.5. System cost

Under multiple uncertainties in the related factors and parameters, solution of the objective function values ($f_{opt}^{\pm}$ = RMB¥ [173.51, 237.49] $\times 10^{12}$) represents two extremes of net system cost over the planning horizon. Conventionally, as the actual value of each continuous variable varies within its lower and upper bounds, the net system cost would change correspondingly between f_{opt}^{-} and f_{opt}^{+}. Normally, a plan with a lower system cost would correspond to a lower end-user demand and a lower level of projection to economic development and population growth in the study region; however, it would result in a higher risk of violating the system constraints. Besides, the upper bounds of cost coefficients correspond to f_{opt}^{+}, implying that the decision maker has an extremely conservative attitude for estimating the system cost and end-user demand, leading to a low system-failure risk and high reliability level for energy production and supply. Conversely, a plan with a lower system cost would correspond to an optimistic estimation towards energy demand projection and relevant costs (i.e., lower-bound system cost, lower energy demand and lower cost coefficients), which also means that conservative prediction of economic development and population growth over the planning horizon. Hence, a decision with lower system cost could lead to a higher risk of system failure and lower system reliability for meeting energy needs in the study region. This demonstrates that there is a tradeoff between system cost and reliability level for energy resources management. Table 5 represents the solutions for system cost, which is composed of expenses for energy resources purchase, importing power, electricity generation, capacity expansion, CO_2-emission reduction, and penalty for excess CO_2 emission. In practice, planning for the high-bound system cost would lead to a lower risk of violating the allowable CO_2 emission level. Conversely, planning for the low-bound system cost would lead to a higher probability of violating the allowance. Therefore, there is a tradeoff between the system cost and CO_2 emission-allowance violation risk.

4.6. CO_2-reduction efficiency

CET is one of the measures to achieve the CO_2 emission reduction targets. However, it is essential to decrease CO_2 emission by using advanced technologies in each power plant. Accordingly, it is critical to discuss the complicated relationship between system cost and various CO_2-reduction efficiency level (SF_k) in response to CET planning in EPS of Beijing. By solving FIMP model, it is obvious that the optimized system costs would have changes with the fluctuation of CO_2-reduction efficiency level. Fig. 5 declares the optimized system costs of the model under different CO_2-reduction efficiency level. There would be a downward tendency of optimized system cost over the planning horizon. For example, the system cost would decrease from RMB¥ [309.28, 385.01] $\times 10^{12}$ when $SF_k = 0\%$ to RMB¥ [211.07, 275.55] $\times 10^{12}$ when $SF_k = 60\%$. Then, the graph throws a new light on the situation. For example, the system cost would increase from RMB¥ [215.36, 279.77] $\times 10^{12}$ when $SF_k = 70\%$ to RMB¥ [223.93, 288.53] $\times 10^{12}$ when $SF_k = 90\%$. It is obviously that CO_2 emission permits for each power plant would be optimized through CO_2 emission permits trading scheme, and the trading scheme would be more effectual under the condition that the CO_2-reduction efficiency level equals to 60%.

Excess CO_2 treated by different power plants would be various under different CO_2-reduction efficiency levels, as shown in Fig. 6. For example, the amount of excess CO_2 treated at cold-fired power plant would decrease from [29.31, 30.60] $\times 10^6$ t when $SF_k = 0\%$ to [15.10, 15.58] $\times 10^6$ t when $SF_k = 60\%$. From reduction efficiency level reaching to 60%, there was a gradual tendency for excess CO_2 treated at coal-fired power plant. The amount of excess CO_2 treated at coal-fired power plant would be the same ([15.10, 15.58] $\times 10^6$ t) when CO_2-reduction efficiency level changes from 60% to 90%. When CO_2-reduction efficiency level equals to 60%, the excess CO_2 treated in cold-fired power plant would be achieved. Otherwise, Fig. 7 describes the excess CO_2 treated at hydropower plant. Comparing to coal-fired power plant, hydropower plant would have a low level of excess CO_2 treated. As the reduction efficiency increasing, there is a steadily decreasing tendency of the amount of excess CO_2 treated at hydropower plant. For example, the amount of excess CO_2 treated in hydropower plant would decline from [27.15, 59.02] $\times 10^3$ t when $SF_k = 0\%$ to [2.71, 5.90] $\times 10^3$ t when $SF_k = 90\%$. It indicated that the higher the reduction efficiency level reached, the lower

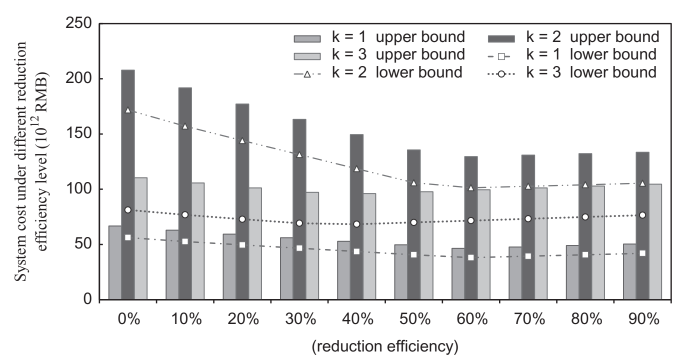

Fig. 5. System cost under different reduction efficiency level.

Table 5
Each activity expense 10^9 RMB¥.

	Time period		
	$k=1$	$k=2$	$k=3$
Cost for purchasing energy	[2787.07, 5736.38]	[4121.44, 14307.79]	[9047.31, 21734.193]
Cost for capacity expansion	[729.06, 1476.23]	[1087.49, 3493.00]	[634.52, 1394.01]
Operating cost for electricity generation	[584.31, 630.63]	[580.83, 635.43]	[552.72, 633.02]
Cost for electricity transmission	[1.16, 1.25]	[1.21, 1.31]	[1.28, 1.38]
Cost for CO_2 reduction	[8404.07, 9149.43]	[9389.17, 10211.28]	[10581.28, 11497.41]
Penalty for excess CO_2 emission	[22926.42, 24252.99]	[82163.52, 87565.08]	[41038.76, 44148.54]

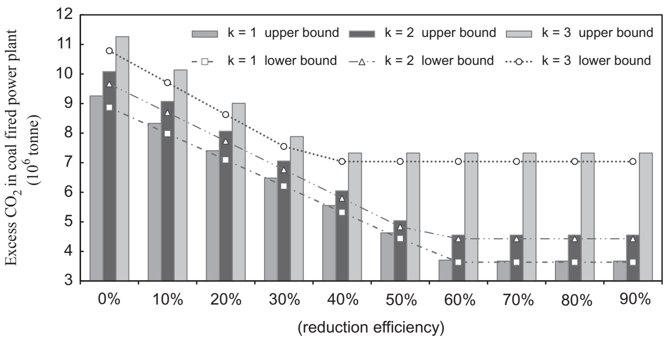

Fig. 6. Excess CO_2 treated in cold-fired power plant.

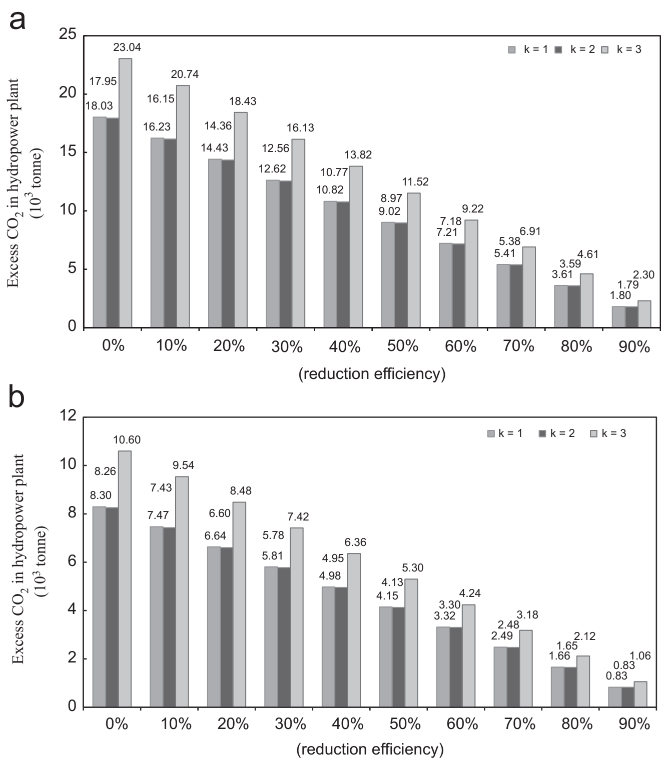

Fig. 7. Excess CO_2 treated in hydropower plant. (a) Upper bound and (b) Lower bound.

the amount of excess CO_2 which should be treated. This is due to the following facts: when the reduction efficiency level is low, the CO_2 emission permits allocated to each power plant are relative low. So, less CO_2 surplus from each power plant would be treated, and low system cost would be gained. However, these scenarios may lead to lower CO_2 reduction level.

5. Discussion

The FIMP-CET model provides a linkage to pre-regulated management policies that have to be followed when a modeling effort is undertaken. If not considering CET planning, it can be converted into a FIMP-based electric power systems planning (FIMP-EPS) problem. The solution of $f_{opt}^{\pm}$=RMB¥ [196.13, 262.08] $\times 10^{12}$ from FIMP-EPS indicates that the obtained system cost is higher than that from the FIMP-CET model. The system cost under trading scheme is obviously lower than that under non-trading scheme. Since the emission trading factors are not addressed in the FIMP-EPS model, the relevant constraints are relaxed. Moreover, in order to meet the discharge limit of total CO_2 emissions, excess CO_2 should be treated by other measures, such as capture and storage, chemical absorption etc., which may further increase the system cost. In comparison, considering CET, the FIMP-CET model can effectively reduce system cost. To ensure the constraints to be satisfied under all interest rate levels, stringent constraints are used in FIMP-CET, although this might raise the system cost. In FIMP-CET, CO_2-emission permits for each power plant are optimized through CO_2 emission permits trading scheme, and the trading scheme would be more effectual under the condition that the CO_2-reduction efficiency is around 60%. This may also lead to the changing of the system cost for EPS. Therefore, CET is effective for CO_2 permit reallocation, and different policies for CO_2 management are associated with different levels of CO_2 management cost and CO_2 mitigation-failure risk.

Compared with the previous studies, the FIMP-CET model has the following advantages. Firstly, the FIMP-CET has advantages in uncertainty reflection and policy analysis, particularly when the input parameters are provided as crisp intervals, functional intervals and probabilistic distributions. The conventional IPP method can only tackle intervals with fixed lower and upper bounds. In the FIMP, constraints can be adjusted in response to the fluctuations of external factors. The infinite objectives can be converted into a single one and the infinite constraints can also be transformed into finite ones. Secondly, this is the first attempt to introduce CET into Beijing's EPS to mitigate CO_2 emissions through the developed FIMP method. Electric power industry is one of the major sources of CO_2 emission in the City of Beijing. It is necessary to accumulate relevant experience to provide a reliable basis for establishing a regional CET market.. The model also incorporates existing international CET policies directly into optimization process. It improves upon the existing approaches for managing CO_2 emissions with trading scheme of EPS, such that robustness of the optimization process can be enhanced. Third, through managing CO_2 emissions with trading scheme of EPS in Beijing, cost-effective options are obtained based on a least-cost strategy with a minimized economic cost and a maximized electricity-supply security. The obtained solutions provide more practical decision bases for formulating CO_2-reduction policies and assessing the associated economic implications in purchasing emission permits or bearing economic penalties. The continuous variable solutions are related to decisions of energy supply, electricity supply, carbon quota and capacity expansion, the interval solutions can help decision makers obtain multiple decision alternatives, and the binary-variable results represent the decisions of facility expansion. Thus, decision makers can adjust the existing demand and supply patterns of energy resources, generate facilitate dynamic analysis for capacity expansion, and coordinate the conflict interactions among economic cost, system efficiency, pollutant mitigation and electricity-supply security, which can help analyzing various policy that are related to different levels of economic penalties when the pre-regulated electricity generation schemes are violated.

There are several assumptions for formulating the FIMP-CET model, which may bring some limitations for managing CO_2 emissions with trading scheme of EPS in Beijing. First, normal distribution is assumed to the availability of electricity demands for the city; in probability theory, according to law of large numbers and central limit theorem, any random event approximates a normal distribution when the samples' number is greater than a certain number. Second, capacity expansion of each power conversion technology is limited to once within the planning horizon; this is due to the fact that the expansion capacity of each power conversion technology is restricted by the condition of finance investment and facility service life. Third, each

community in the city has the same economy and energy structures; if each community is considered as different economy and energy structures such that more complexities would be generated which may beyond the model's mathematical expression capacity.

Besides, techniques of post-optimality analysis (e.g., multi-criteria decision analysis, analytical hierarchy process technique, dual programming, and parametric programming) could be used for further supporting fine adjustments of the modeling results and thus for enhancing their applicability to practical situations [64,65].Furthermore, intelligent decision support system (IDSS) could be developed based on an integration of optimization modeling, scenario development, user interaction, policy analysis and visual display into a general framework. Uncertainties in CET systems could be effectively reflected and addressed through the full-infinite interval-stochastic mixed-integer programming (FIMP) method, improving the robustness of the IDSS for real-world applications. Thus, it can be used as an efficient tool for analyzing and visualizing impacts of CET policies, regional sustainable development strategies, and CO_2 emission reduction measures in an interactive, flexible and dynamic context.

6. Conclusions

In this study, a full-infinite interval-stochastic mixed-integer programming (FIMP) method has been developed for planning carbon emission trading (CET) under dual uncertainties. FIMP incorporates two-stage stochastic programming (TSP) and interval full-infinite programming (FIP) within a general framework. FIMP has advantages in uncertainty reflection and policy analysis, especially when the input parameters are provided as crisp intervals, functional intervals and probabilistic distributions. This study attempts to introduce CET into the Beijing's electric power system (EPS), and tries to give analysis of following questions: (i) how to determine initial distribution of permits and sector coverage for Beijing's domestic power market, (ii) how to quantify the final system cost of each power conversion technology under CET, and (iii) how to ascertain the amount of electricity supply and CO_2 mitigation.

Then, a FIMP-based carbon emission trading (FIMP-CET) model has been formulated for planning CO_2 emissions with trading scheme under dual uncertainties of electric power system (EPS) in Beijing. This is the first attempt to introduce CET into Beijing's EPS to mitigate CO_2 emissions with optimization model. With the aid of model, the schemes about energy supply, electricity supply, carbon quota, and capacity expansion have been obtained. Results are helpful for supporting (a) evaluation or improvement of allocation patterns of energy resources, (b) formulation of local policies regarding energy consumption, electricity supply, economic development and energy structure, and (c) resolving of conflicts and interactions among CO_2 reduction, economic cost, system reliability and energy-supply security.

The results obtained suggest that the study city should making efforts to improve its policy in the following several manners. Firstly, encourage renewable energy (such as hydropower, wind power, photovoltaic power and biomass power) actively, such that full implementation of these measures can alleviate the contradiction among energy supply, energy demand, and CO_2-reduction. Secondly, improve CO_2-reduction efficiency (e.g., installation of CO_2-reduction facilities) and increase energy-conversion efficiency, which can evolve the international influence of the city fundamentally. Finally, the study of CO_2 capture and storage technology should be strongly advocates for achieving to the city's commitment reduction.

Acknowledgments

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